

Hierarchical Transformers with Delta-Attention for Multimodal Fusion

Kunjal Panchal, 32126469, kpanchal@umass.edu

1 Problem Statement. In human-computer interaction; the tasks like emotion recognition, sentiment analysis, personality trait recognition, audio source localization, audio diarization are very important for the use cases like product and advertisement market value analysis, personal assistant to the people with visible or invisible disabilities and such. The task of emotion recognition has attracted attention of the machine learning community [4,8]. Emotions can be detected from facial expressions, from speech patterns, and from words uttered. The issue with analysis of any one mode of expression (Visual, Verbal or Vocal) is that lot of contextual information can get lost [2,15]. E.g., a sarcastic remark like “That sounds great” can be uttered with a smirk, in an angry or indignant voice. If we only analyze the verbal modality, we would miss the context of the situation (imparted by visuals and vocals). This asks researchers to inspect multiple modalities to get a thorough understanding of the cross-modal dependencies and temporal context of the situation to analyze the emotion. [18]

2 Related Work. To combine the most widely observable modalities: visuals, vocals and verbals; there are different ways proposed like hidden markov models [19], fine Gaussian support vector machines [5], deep belief network [5,9]. The deep learning models provided much better accuracy and understanding. Graph fusion based network [14] where the powerset of all the modalities create a graph structure and each representation of a node fuses with all others; clearly, they do not scale well with the increment in modalities, tensor fusion based network [18]; a promising path, current research is going on in lowering the amount of tensor computations, LSTMs + CNNs [6,13,17,22,25,26] are the most popular but suffers from the lack of long-range dependencies and their unaligned nature as discussed further in the next section.

3 Novelty. For all the approaches taken so far, the below mentioned missing gaps will be addressed in this project. In RNNs, looking at the entire sequence of data and outputting the last, single hidden state as its representation, often turns into the model forgetting information way past the current timestamp. They don’t preserve the *long-range dependencies* [21]. Second, data can be unaligned across modalities. A frowning face may relate to a pessimistic word spoken in the past. It’s not always between current word and current expression. And thus, third related point is, neutral expressions are quite idiosyncratic [7]. Some people may always look angry given their facial configuration. This raises the need for *delta attention* [25], we need to take cross-modal context plus the temporal context within each individual modality to negate the effect of “monotonous-across-the-time” features.

And lastly, the mechanism of fusing the modalities itself is not clearly figured out, the papers focusing on late fusion [11,16] fall short in making any cross-correlation between the effect of each modality on the classification, generally early fusion methods [10] have been proven superior, this project focuses on building a hierarchical transformer architecture where each modality has some representation vectors inferred by delta self-attention unimodal modules, which will be fused together with a deep cross correlation analysis [DCCA] [12,20] module and finally processed with a cross-attention module to classify multiple modalities into 6 emotion classes: happy, sad, anger, surprise, disgust, and fear.

4 Methodology. This project will experiment with transformers like BERT [3] and auto-regressive transformers like XLNet [24], from Huggingface [23], where each feature has a vector representing its dependency across all other features in a sequence. This is ideal for the verbal modality, because a big language model trained on 33B tokens will have sufficient knowledge on textual entailment and contradiction. While for visuals and vocals, a delta-attention based RNN will be a good starting point. Once these three representations are learned, they can be fused together with a DCCA module [20] to get a cross-modal representation. This representation will be finally fed into a cross-attention transformer module alongside the skip connections from individual representations. Finally a fully connected layer connecting as the bridge between a softmax layer and the cross-attention module can classify the emotion classes. These hypotheses on adding a delta-attention to fuse the modalities with a correlation analysis will be proved fair if we can achieve a good F1 score on the classification task, which can compete with the research done without the use of delta-attention [18,21].

5 Data Sets. Multimodal Opinion Sentiment and Emotion Intensity [CMU-MOSEI]¹ [1] is the largest and the latest dataset of sentence level sentiment analysis and emotion recognition. It contains more than 65 hours of annotated video from more than 1000 speakers and 250 topics. It has around 23k samples, each with around 1000 text features, 300 visual frames, and 150 acoustic features. Most of the transformer based papers have been benchmarked on this dataset, because of its size and the variety in “in-the-wild” emotions. Thus, this project will also use this dataset, to be able to compare the results fairly.

¹<https://github.com/A2Zadeh/CMU-MultimodalSDK>

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